

Article

Estimating Public Charging Demand of Electric Vehicles

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Received: 18 September 2019; Accepted: 22 October 2019; Published: 24 October 2019

Abstract: Electric vehicles require sufficient public charging infrastructure. This in turn necessitates detailed information on charging demand. In this paper we present a four-step approach to estimating public charging demand of electric vehicles. Previous methods are limited in their ability to provide differentiated results and adapt to future developments. Therefore, we account for user groups (private, carsharing, commercial), technical developments (vehicles, infrastructure), infrastructure availability, and carsharing development (operational area, business models, autonomous vehicles). Our approach also considers the interactions between these factors and allows for scenario analysis yielding the quantity and spatial distribution of public charging demand. We demonstrate our approach for Berlin, Germany. We find that the majority of public charging demand results from carsharing. This demand is concentrated in the city center, even when carsharing is available citywide. Public charging demand for commercial users is relatively low and located outside the city center. For private users, public charging demand shifts to the city center with an increasing market penetration of electric vehicles and technological advancements (increased range, charging speed). Public demand from private users increases dramatically when private infrastructure is absent. Finally, public charging demand shifts to the city center when private users do not have private infrastructure.

Keywords: electric vehicles; charging demand; public charging infrastructure; autonomous vehicles; carsharing

1. Introduction

1.1. Introduction

Numerous approaches have been developed to estimate public charging demand of electric vehicles. However, it is not clear who will use the bulk of electric vehicles and how they will be used. Private users can modify their travel behavior to some extent, but their public charging is strongly affected by the ability to charge privately at home. Flexible carsharing users typically only complete a single trip and these vehicles require public charging infrastructure. Finally, commercial users follow fixed routes and may have access to private infrastructure. Thus public charging demand will very likely differ based on the user group in question. Differences in charging demand per user groups are not yet known.

In addition to user groups, technological developments (e.g., range and charging technology), autonomous vehicles, development of carsharing, infrastructure availability, and numerous other factors will strongly affect the amount and spatial distribution of public charging demand. The interactions between these factors are also critical. Previous approaches to determine the charging

demand are limited in their ability to account for these factors and, thus, to adapt to future developments.

Consequently, we present a new approach to determine charging demand considering user-groups, technological developments, autonomous vehicles, carsharing, infrastructure availability, and spatial distribution. This approach is user-focused and allows for scenario analysis. This enables us to identify future characteristics of charging demand for different user groups and scenarios to support a demand-oriented expansion of public charging infrastructure.

1.2. Literature Review

Electric vehicles can reduce greenhouse gas emissions assuming they utilize electricity from renewable energy sources [1–5]. However, the lack of sufficient infrastructure is a major barrier to the adoption of electric vehicles [6, 7]. Given the importance of charging infrastructure, there are numerous approaches to determine the quantity and location of public infrastructure. These approaches are either demand-oriented (i.e., simulation-based) or supply-oriented (i.e., optimization-based).

1.2.1. Demand-Oriented Approaches

We first review the demand-oriented approaches. The demand-oriented approaches can be divided into three categories: activity-based models, behavioral models, and traffic flow models. Using an activity-based approach, Dong et al. investigate whether BEVs are suitable for daily activities using empirically collected road data via GPS tracking [8]. They calculate optimal locations for charging infrastructure and conclude that locating charging infrastructure based on daily activities can increase BEV usage. Cavadas et al. examine activity behavior from empirical data [9]. In addition to modeling travel activities, they include the demand transfer, which would occur due to the occupancy of the charging infrastructure by other vehicles. Brooker and Qin use national travel survey data to determine the charging demand [10]. Paffumi et al. use real-world driving data from conventional fuel vehicles to estimate charging demand [11].

Similar to activity-based research, behavior-based studies focus on the behavior of vehicle users. The difference, however, is that only certain sections of daily activities are considered. Chen et al. use empirically measured parking behavior in zones where charging infrastructure locations should be placed [12]. The location and length of parking events are used as variables to calculate the demand for charging infrastructure. Helmus and van den Hoed, on the other hand, look at charging behavior [13]. They develop a typology of charging behavior to identify specific charging patterns in specific locations. Yang developed a user-choice model to locate fast-charging stations and provides insights into user-choice models [14]. Gnann et al. estimate fast-charging infrastructure needs analyzing current charging behavior from a large charging data set and queuing model [15]. Other work by Gnann, Plötz and Wietschel utilizes an agent-based market diffusion model [16].

In comparison to these approaches, other studies use traffic flow simulations to estimate charging infrastructure. Li and Huang present a traffic flow based selection model, including possible routes between origin and destination [17]. Building on this, they develop an infrastructure model that minimizes the cost of long-distance transportation for electric vehicles. He et al. describe charging as multi-class network equilibrium flow pattern, which they solve using an iterative procedure to determine infrastructure location [18]. Finally, Olivella-Rosell et al. use an agent-based model to determine electric vehicle charging demand [19].

1.2.2. Supply-Oriented Approaches

Next, we review the supply-oriented approaches. The supply-oriented approaches focus on optimizing fleets and scheduling at specific stations, assuming that the charging locations are predefined. Sathaye and Kelley develop a continuous optimization approach to identify the minimum charging infrastructure along highway corridors [20]. Lam et al. generate charging infrastructure selection zones that simultaneously minimize construction costs and optimize coverage [21]. Tian et al. optimize station location considering charging behavior [22]. They find that prior to optimizing station location, charging behavior must be forecast.

Chen and Hua use gas station locations as candidate sites, which are then rated according to a set-coverage and spatial-load forecasting model [23]. Frade et al. studied the location of infrastructure using a methodology of maximum coverage to optimize demand covered [24]. Using the battery capacity and associated charging capabilities Nie and Ghamami develop a method to reach a certain pre-established level of service [25]. Yao et al. set the route choice of electric vehicle users in relation to the state-of-charge (SOC) in order to arrive at a level of service location model [26]. Finally, Jung et al. utilize a simulation-based optimization problem to determine infrastructure location for shared electric taxis [27].

1.3. A New Approach

Consequently, numerous studies focus on the general evaluation of infrastructure to support electric vehicles. However, these approaches do not sufficiently account for user groups, technology developments, autonomous vehicles, carsharing, infrastructure, and the interactions of these factors now and in the future. Therefore, we present a four-step approach to account for these factors, their interactions, and future scenarios. Applying the approach to a case study, we determine the quantity and spatial distribution of charging demand differentiated by these factors in anticipated future scenarios.

The rest of the paper is structured as follows. Next we present the methodology, which outlines our four-step approach to estimating public charging demand. To illustrate our approach, we apply it to the case study of Berlin, Germany. We present the data, models, and the development of the scenarios. After applying the approach to Berlin, the results are summarized. This is followed by a discussion and recommendations. Finally, we present conclusions of the work, identify limitations of the research, and present future areas for continued investigation.

2. Methodology

There are four steps in our approach to estimating public charging demand of electric vehicles (Figure 1). The approach accounts for three user groups: private, carsharing, and commercial. First, existing transport models generate input data (Step I). These data represent mobility demand for each user group. Second, these data are combined with user group input data to generate enhanced input data (Step II). These user group input data are determined from previous studies and existing empirical data sources. The enhanced input data include probabilities of using electric vehicles based on empirical data. Third, based on findings from qualitative expert interviews, scenarios are developed independently from the input data and are the same for every user group (Step III). Fourth, we develop charging behavior models to simulate the charging demand for each user group (Step IV). The models use the enhanced input data and are run for each scenario resulting in charging demand. Figure 1 provides an overview of our approach.

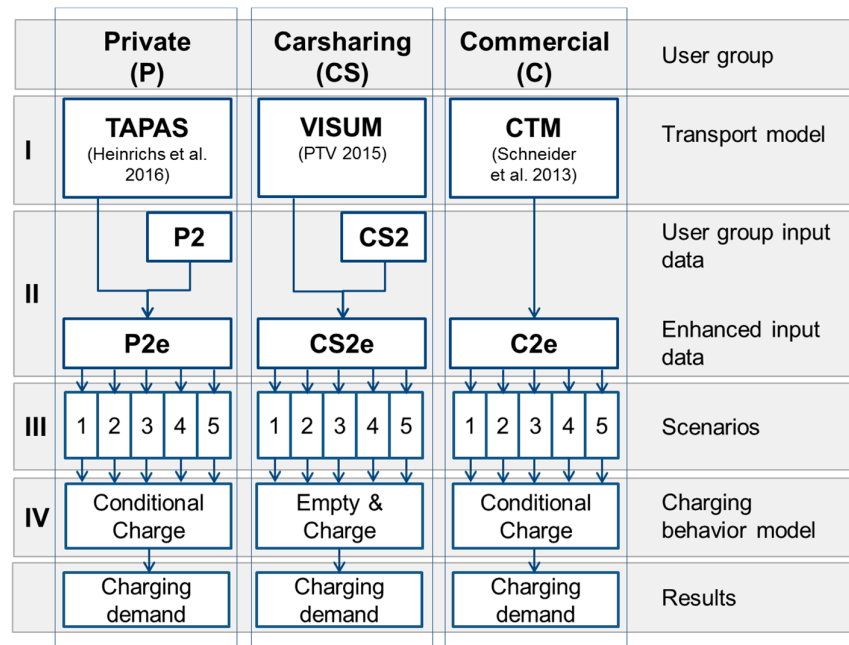


Figure 1. Overview of our four-step approach to estimating public charging demand. Step I—Transport models generate input data. Step II—Enhanced input data added. Step III—Scenario development. Step IV—Charging behavior models simulate charging demand. (Abbreviations: TAPAS—Travel Activity Patterns Simulation, VISUM—Macroscopic traffic model of Berlin, CTM—Commercial Transport Model).

In order to illustrate our approach, we apply it to Berlin. This case study allows us to utilize data on electric vehicles, electric vehicle users, mobility behavior, urban structure, and other relevant factors. We select Berlin as the case study, due to the availability of detailed models (i.e., travel simulation models) and data (i.e., electric vehicle users, carsharing programs, carsharing user data). Furthermore, Berlin is one of Europe's metropolitan areas with a dynamic market of flexible carsharing. The municipality of Berlin also supports electric vehicles and flexible carsharing through public charging infrastructure, which allows for the application of our approach.

As context for the case study, Germany aimed to have one million electric vehicles on the road by 2020 and six million by 2030 [28]. By 2020 the government wants 100,000 public charging points, of which a third should be fast-charging points [29]. As of October 1, 2019, there are 145,933 battery-electric vehicles (BEVs) and 115,623 plug-in hybrid electric vehicles (PHEVs) for a total of 261,600 electric vehicles in Germany [30]. In the next sections, we outline the four-steps in our approach.

2.1. Step I—Transport Models Generate Input Data

We first select existing transport models to generate the model input data. In general, these data have the form of origin-destination-matrices with differing specifications regarding the trip, the person, the household or company, and partially provide trip-chains. The models and the resulting data are organized by user group below.

2.1.1. Private Users

In order to determine the mobility demand for private users, we use the Travel and Activity Patterns Simulation (TAPAS) model [31]. This demand model utilizes a synthetic population, which represents a realistic representation of the population from different data sources accounting for socio-economic and demographic characteristics of persons and households. In the simulation, each person is assigned a daily schedule with individual activities for that day.

The output of this model is the entire traffic demand for one day in Berlin structured in complete trip chains for each person. These trip chains are essential when using the person and household-related behavior throughout the entire day. Each trip includes several parameters, such as mode of transport, purpose, origin and destination, and personal and household information. We use a subset of 4.3 million trips (only car trips)

2.1.2. Carsharing Users

To generate model input data for carsharing, we utilize VISUM, the official macroscopic traffic model of Berlin [32]. This model provides origin-destination-matrices for motorized transport for the spatial layer of transport cells. The data include information on trip purpose, but there is no information on trip-chains. We utilize these fine-grained purpose-related origin-destination matrices to refine user-group-specific input data gathered from several different sources. The core of this method uses the Berlin dataset from the municipal household travel survey System of Representative Traffic Surveys [33]. This municipal dataset includes information on geocoded trips, households, and person for more than 40,000 participants.

2.1.3. Commercial Users

Commercial users of electric vehicles are limited to passenger transportation and light commercial vehicles. Traffic demand for commercial transport is generated using the Commercial Transport Model (CTM) [34]. Here we use a methodology that carries out a single simulation for each vehicle based on trip diaries. Iterating for all vehicles, all passenger and freight traffic with light commercial vehicles is generated for an average workday in Berlin.

In order to address the fine-grained pattern of passenger and freight transport with light commercial vehicles, a synthetically generated economic structure is used as a basis for the model in which the companies in the study area are located at actual buildings. The number of trips, and consequently, the number of vehicles per company in the study area is determined on the basis of average data. These trip chains are then transferred to the area under consideration in the model so that exact time and spatial resolution is possible. We use these geocoded trip chains with information about the company as model output data. As companies' specifications for both using electric vehicles and the model output are less explicit than for other user groups, we do not enhance the model output data with probabilities for commercial users.

2.2. Step II—Enhanced Input Data Added

In the second step, further user group input data are determined from previous studies and existing empirical data sources to enhance data resulting from the transport models. This step allows assigning probabilities of using electric vehicles for each trip based on empiric data which is essential for the simulation. We do this for private and carsharing users.

2.2.1. Private Users

For private users, we use data from the study First Users of Electric Vehicles in Germany [35] to estimate the probability of using an electric vehicle based on sociodemographic and spatial data. This allows us to utilize the first census of real-world electric vehicle users without relying on simulation model results. Next, the distribution of personal and household sociodemographic data is identified. The study also shows a connection between the residential structure and electric vehicle procurement [35]. To enable a more realistic allocation of electric vehicle probabilities, the residential addresses of households are supplemented by private parking data. To estimate the allocation of electric vehicles based on sociodemographic data and the availability of private parking, “early-adopter weighting” is developed which takes both variables into account (i.e., sociodemographic data and availability of private parking). We define a second weighting according to the empirical distribution of electric vehicle users with probabilities of electric vehicle use (“early-majority weighting”) using only sociodemographic data. This weighting is later used to

analyze the demands of early private users without private charging infrastructure. Based on this, we determine the trips done by electric vehicles for different diffusion rates and different significance of private charging infrastructure.

2.2.2. Carsharing Users

The carsharing data is enhanced with estimated probabilities of using carsharing for each trip. To approximate the probability of using carsharing, we analyze the profiles of current users of carsharing, as well as characteristics of trips which are currently done by carsharing. We use data from a survey with a random sample of 1,071 users of flexible carsharing in Berlin for socio-demography data and an in-car survey with 2,850 recorded trips for trip characteristics (“baseline weighting”) [36].

As a result, the weighted data approximates the carsharing demand based on the socio-demography of carsharing users and the route characteristics of the carsharing trips traveled. This represents the present state of carsharing users. To foresee future developments of carsharing, we develop a broader weighting (“established weighting”) where the probability distribution of users’ sociodemographics and trip characteristics are widened. The output of this method is an origin-destination matrix of trips in Berlin assigned with the probability of using a flexible carsharing vehicle for this trip as described above. These data do not include trip chains as vehicles are used by several different drivers.

2.3. Step III—Scenario Development

Having determined the input data above, we now present the scenario development. The scenarios are determined using expert interviews. This step is performed independently from the quantitative data used. We use a structured interview of twenty experts for their assessment in six areas. The first three areas are market diffusion (expected number of electric vehicles), dissemination of BEVs versus PHEVs, and anticipated user groups of charging infrastructure. The remaining areas are the psychological aspects of charging infrastructure, desired charging speeds, and locating public charging infrastructure. The interview questions and associated information are developed based on a literature review (e.g., Reference [37]).

We conduct a qualitative analysis of the interview results. The analysis shows that there are diverging and partly contradictory opinions on key variables. Hence, different future developments seem feasible. Thus, the interviewees’ statements were condensed to individual future scenarios, mediating within clusters of similar future perception, but keeping contrary opinions. Thus, expert interviews are used to determine the five scenarios presented below. They vary the diffusion of electric vehicles, technical characteristics, user behavior, and carsharing business models. Each scenario accounts for the three user groups resulting in fifteen future development pathways for public charging demand. Table 1 provides an overview of all parameters varied in the different scenarios.

2.3.1. Baseline

The “Baseline” scenario describes the current situation in Germany. The fleet size corresponds to the information provided by the German Federal Motor Transport Authority [30] and is divided into private and commercial use according to the results of Frenzel et al. [35]. For the allocation of the private vehicles, the “early-adopter weighting” is used. Accordingly, all private and commercial users have access to private charging infrastructure. The potential for carsharing is weighted according to the sociodemographic profile of current users following the “baseline weighting.” AC charging technology (AC) is used in all cases, and the charging speed is 5 kilometers per minute. The gross range of vehicles is 150 km, and carsharing vehicles must be charged if the SOC is less than 25% at the end of a trip. If a carsharing vehicle is not used for 72 hours, it is relocated to an area of more activity.

2.3.2. Trend-AC 2030

For the “Trend-AC” scenario, the fleet expands to 6,350 vehicles with the same ratio between private and commercial vehicles as foreseen by the experts. For the carsharing business model, we introduce a relocation incentive which motivates users to move inactive carsharing vehicles. For the simulation, this results in the modeled movement of carsharing vehicles after 24 hours of inactivity. This is based on future plans from carsharing fleet operators.

2.3.3. Trend-DC 2030

The “Trend-DC” scenario determines the influence of charging speed on charging demand. For this scenario, we increase the charging speed to 10 km per minute. We label this scenario DC charging, but the scenario also accounts for fast AC charging infrastructure meeting the required charging speed.

2.3.4. Accelerated 2030

In comparison with the “Trend-DC” scenario, in the “Accelerated” scenario, the group of private users is extended to users without a private charging option. The early-majority assignment of vehicles means that they are allocated only on the basis of sociodemographic factors (“early-majority weighting”). In contrast to the scenarios described above, private charging is not used as an allocation criterion.

2.3.5. Autonomous Driving

The “Autonomous Driving” scenario combines optimistic expectations regarding the development of the vehicle stock with future technological advances. There are 15,000 private and commercial vehicles and 5,000 carsharing vehicles. This scenario approximates the automation of a fleet of electric taxis. This is accompanied by expanding the operational area of carsharing to the entire city and using the established group of carsharing users (“established weighting”). The range of the vehicles is increased to 350 km. After ten minutes of inactivity, carsharing vehicles drive to the next demand location. This reflects the autonomous carsharing fleet where vehicles autonomously pick up the next passenger. At the same time, the remaining range until the vehicle has to be charged reduced to 10 km (3%) because no user-bias has to be taken into account.

Table 1. Summary of the five scenarios.

	1. Baseline			2. Trend-AC			3. Trend-DC			4. Accelerated			5. Autonomous		
Pathway	1P	1CS	1C	2P	2CS	2C	3P	3CS	3C	4P	4CS	4C	5P	5CS	5C
User group	Private	CS	Comm	Private	CS	Comm	Private	CS	Comm	Private	CS	Comm	Private	CS	Comm
Fleet size	510	306	350	3510	500	2340	3,510	500	2,340	3,510	500	2,340	9000	5000	6000
Charging technology	AC	AC	AC	AC	AC	AC	DC	DC	DC	DC	DC	DC	DC	DC	DC
Range (km)	150	150	150	150	150	150	150	150	150	150	150	150	350	350	350
Operation area	Small			Small			Small			Large			Large		
CS Relocate	72 h			24 h			24 h			24 h			10 min		
Charging simulation model	Cond	E&C	Cond	Cond	E&C	Cond	Cond	E&C	Cond	Cond	E&C	Cond	Cond	E&C	Cond
Min remaining range	25% 40 km			25% 40 km			11% 40 km			11% 40 km			3% 10 km		
Assign	EA	Base-line		EA	Base-line		EA	Base-line		EM	Est		EM	Est	

("Baseline," "Trend-AC," "Trend-DC," "Accelerated," "Autonomous Driving"), three user groups (Private, Carsharing, Commercial), and resulting in fifteen pathways (e.g., 1P, 1CS, 1C). (Abbreviations: Assign—assignment, Comm—commercial, CS—carsharing, Cond—conditional, EA—early adopter, E&C—empty and charge, EM—early majority, Est—established, Oper—operational.)

2.4. Step IV—Charging Behavior Models Simulate Charging Demand

Next, we build a charging simulation model to simulate the decision process for charging. This section outlines how the simulation of charging demand is determined. Using different methodology and data for three user groups and five scenarios allow us to estimate individual charging demand. Furthermore, the significance of various future parameters, such as technical characteristics, user behavior, and carsharing business models can be analyzed.

For the simulation, we use two charging behavior models. The first charging behavior model is the simple “empty and charge” model. The second is the more complex “conditional charging” model. The “empty and charge” model functions as follows. If at the end of the trip, the vehicle SOC is below a defined minimum, a virtual charging process is initiated at that location, and the charging demand is documented temporally and spatially. In this case, vehicles are only charged when the SOC is low and charged until the maximum possible charge level is reached (i.e., fully charged). For carsharing users, the “empty and charge” model is used. Vehicles are charged exclusively with public infrastructure.

In comparison, private and commercial users cannot spontaneously charge their vehicles at the end of every trip. Rather, their mobility must be planned to ensure completion of all trips. In addition, early-adopter private users predominantly have their own charging infrastructure. However, in the future, there is also the potential for electric vehicle owners without private charging options. The distinction between the charging location and the charging demand at private infrastructure is thus implemented in the more complex “conditional charge” model (Figure 2). Public charging sites include public streets, as well as semi-public areas (e.g., parking garages).

Figure 2 shows the decision-making process (“conditional charge”) implemented in the simulation. This process is divided into the decision before the trip and the decision after the trip. Before the trip, the simulation checks whether the intended trip can be completed. If the vehicle’s remaining SOC is insufficient, charging is documented (a virtual charge is started) and the trip is postponed until the battery charge level is sufficient to complete the trip. The model asks if a preferred charging point (e.g., private charging infrastructure) can be reached with the remaining range. If not, the parking duration and the achievable SOC are used to check which point within the further trip chain is best to charge at public infrastructure. Places where vehicles are parked for a longer time are more likely to be charging locations. Even if the next preference point is reachable, there is a low possibility of intermediate charging. On the basis of the parking duration and the remaining range, this probability is estimated.

All carsharing vehicles are fully charged on the first day of the simulation. During the course of the day, they are driven to the minimum remaining SOC. Depending on the distribution of the vehicles’ trip chains and the duration of the trips, the charge starts at different times. After the first day, the charging is distributed over the course of a day.

For the analysis, we utilize traffic districts, which are the smallest spatial divisions used for transportation analysis in Berlin. Sensitivity checks of the charging demand between the traffic districts within the simulation days show that the relative distribution of the charging demand between the traffic districts after the transient phase is subject to minor fluctuations. The result is the average daily charging demand, expressed in required charge for kilometers traveled per working day (km / WD). For example, if a vehicle drives a total of 150 km on three days and has to charge on the third day, the third day will require 150 km of charging. The average of the summed charges per day and traffic district after the transient phase gives the average daily charging demand. This average daily charging demand is unit independent of charge type or charging technology.

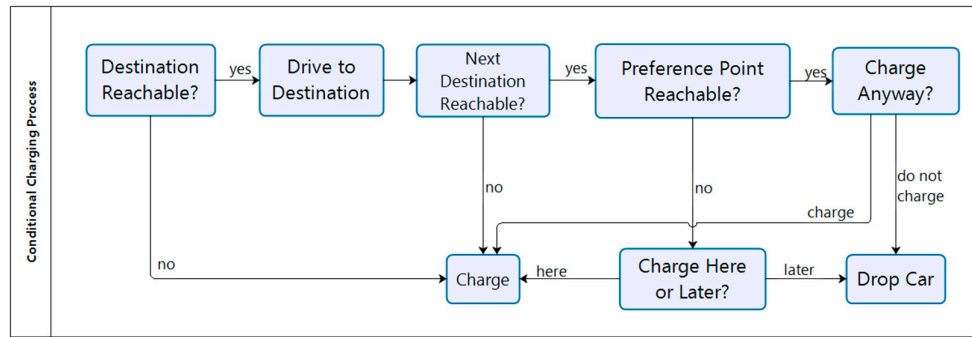


Figure 2. Overview of the “conditional charge” model.

3. Results

3.1. Charging Demand

The charging simulation model is run for different scenarios (Step IV) yielding charging demand. To present the results, the quantity of charging demand for each scenario is visually illustrated (Figure 3).

The “Baseline” scenario has a charging demand of approximately 32,000 km / WD. In contrast, the trend scenarios “Trend-AC,” “Trend-DC,” and “Accelerated” account for around seven times this charging demand (210,000 to 240,000 km / WD). This is mainly attributed to fleet growth. In the “Autonomous Driving” scenario, the charging demand increases to approximately 24 times that of the “Baseline” scenario with 766,000 km / WD. The distinction of charging infrastructure in private and public spaces is presented in Figure 3.

In the “Baseline,” “Trend-AC,” and “Trend-DC” scenarios, the majority of the charging demand is generated at private infrastructure. In the “Baseline” scenario, about 38% of the charging demand arises in public spaces. From the “Accelerated” scenario, the share of public charging demand increases significantly, and in the “Autonomous Driving” scenario it is more than 85%.

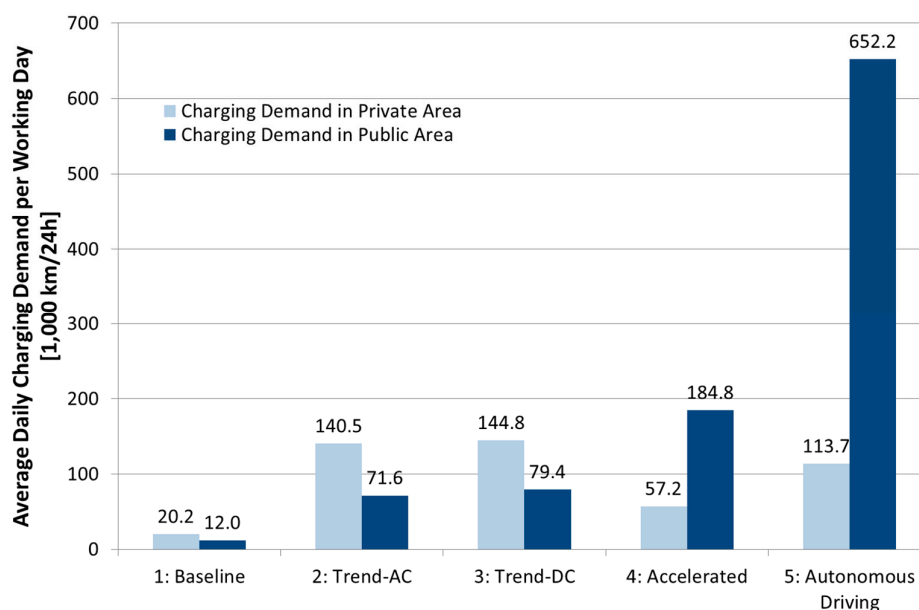


Figure 3. Public versus private average daily charging demand per working day (1,000 km/24h) per scenario.

Figure 4 shows the average daily charging demand per working day in public space according to the user group and scenario. For all scenarios, the majority of public charging demand arises from free-floating carsharing vehicles. In the scenarios “Accelerated” and “Autonomous Driving,” private charging makes up significant shares with 37% and 25% of the public demand. The demand for commercial users is very low and comprises 0.2% and 7% for “Autonomous Driving” and “Trend-AC”, respectively.

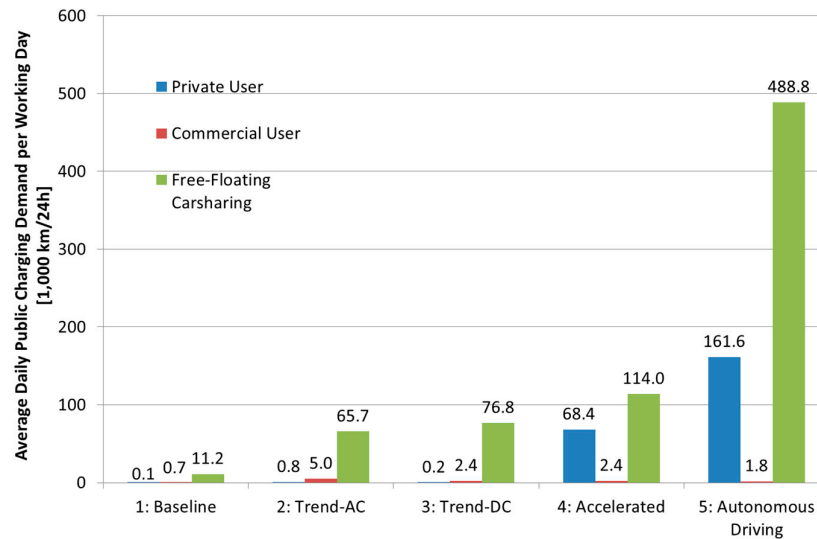


Figure 4. Average daily public charging demand per working day (1,000 km/24h) per user group and scenario.

The simulation results also allow the distinction of the charging demand by location (cell), space (public, private), user group (private, commercial, car sharing) and time (per 15-minute-interval). Figure 5 shows the average charging demand (initialization of the charging process) of the carsharing user group in public space for the overall area. As seen, the charging demand peaks in the afternoon and early evening hours. In the independent system, all charging demand is initiated by users only (no overnight street charging). All scenarios have a similar distribution over the course of the day.

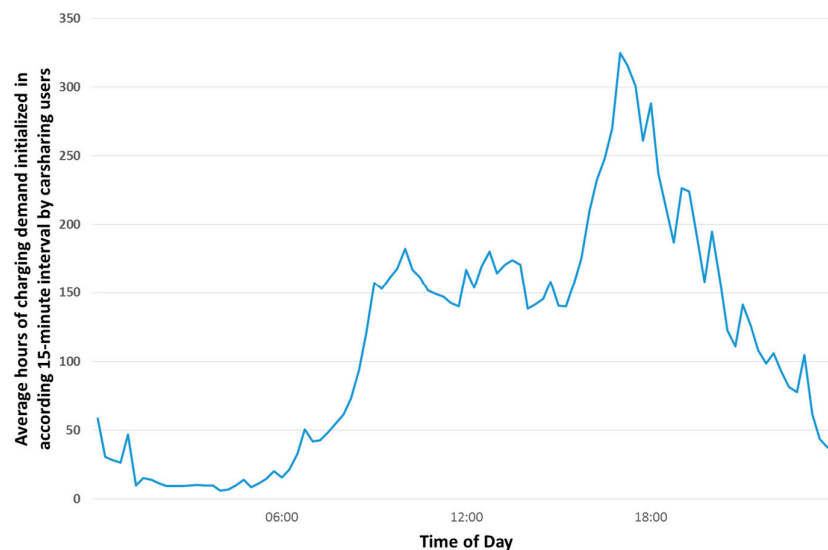


Figure 5. Average charging demand over the course of the day (user group: carsharing, based on 15 minutes interval).

3.2. Spatial Distribution of Public Charging Infrastructure

Next, the spatial distribution of public charging demand is determined for traffic districts in Berlin for the 15 pathways. Representative results are presented in the following paragraphs and figures.

3.2.1. “Baseline” and “Trend-AC” for Private Users

The spatial distribution of public charging demand for the “Baseline” and “Trend-AC” scenarios is similar for private and commercial users. Using the example of private users in the “Baseline” scenario, Figure 6 shows that the outer city, and in particular in the south and north-west, have high demand. As explained earlier, the public charging demand of private and commercial users in the “Baseline” and “Trend-AC” scenario is low. Only seven traffic districts have more than 1 km of public charging demand per day from private users whereas about 333 traffic districts have a charging demand between 0.1 and 1 km. Charging demand for all these traffic districts is mainly due to intermediate charging from range anxiety. After longer trips in the outer city, range anxiety increases, as well as the probability of intermediate charging. The spatial distribution of the charging demand is similar between the “Baseline” and the “Trend-AC” scenarios, and the magnitude of the public charging demand increases in relation to fleet size.

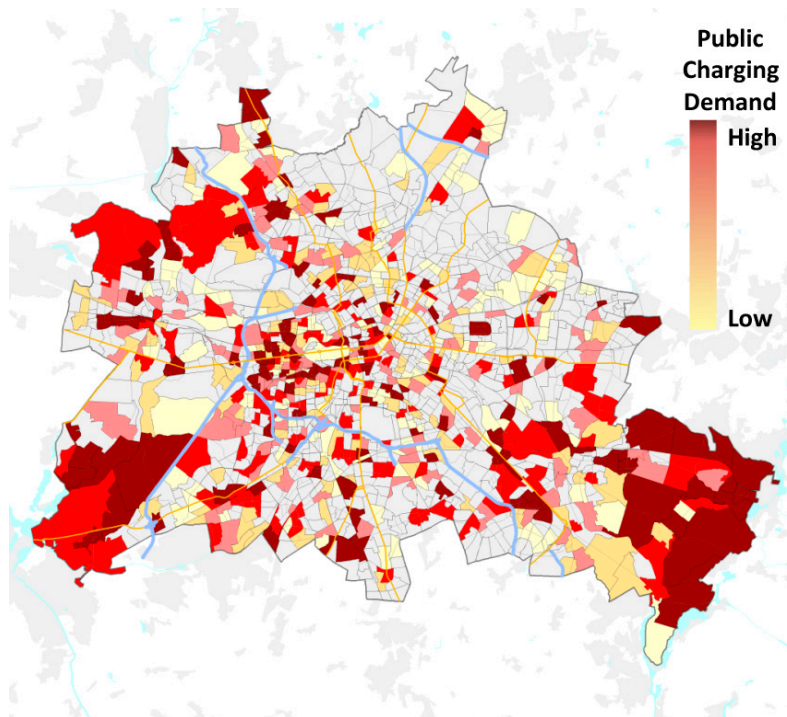


Figure 6. Relative spatial distribution of public charging demand: “Baseline” for private users (Pathway 1P); “Trend-AC” is similar. The map shows the relative distribution of charging demand in Berlin by assigning dark red to the maximum value and scaling the other values in accordance.

3.2.2. “Baseline” and “Trend-AC” for Commercial Users

For commercial users, the spatial priorities are even more pronounced in the outer city (Figure 7). Despite smaller fleets compared to private vehicles, there is higher public charging. Commercial users have longer trips than private users. In addition, daily routes of commercial users consist of more individual trips (often two to three trips) than trip chains of private users. In some cases, charging during trip chains cannot be completed, due to short parking durations of commercial users.

The charging demand for commercial users in the “Baseline” scenario mainly arises due to intermediate charging and the inability to reach the next destination. The traffic district with the maximum average public charging demand from commercial users in the “Baseline” scenario is 13 km per day. The charging demand of the top ten traffic districts is 4 km or more per day. This illustrates the small quantity of public charging. For a vehicle with a 150 km range, the highest charging demand in a traffic district is a single charge every ten days. Only ten traffic districts have a vehicle fully charged more than once a month. In about 80 traffic districts, a vehicle is only fully charged for commercial use once per quarter.

In the “Trend-AC” scenario, the public charging demand of commercial users increases in proportion to fleet size. The spatial distribution remains comparable to the “Baseline” scenario. The traffic district with the maximum demand has a vehicle fully charge every 1.5 days. There are ten traffic districts where a vehicle fully charges every five days, and 100 traffic districts where a vehicle fully charges every two weeks.

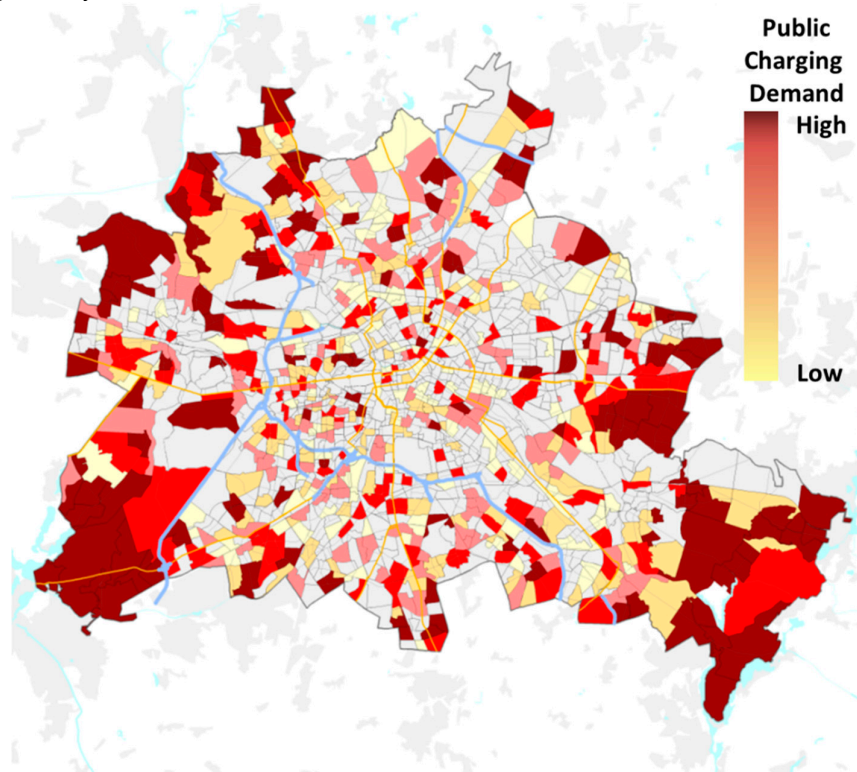


Figure 7. Relative spatial distribution of public charging demand: “Baseline” for commercial users (Pathway 1C); “Trend-AC” is similar.

3.2.3. “Trend-DC” for Private and Commercial Users

Public charging demand for private and commercial users decreases in the “Trend-DC” scenario as private charging infrastructure can be used to fully charge vehicles with shorter parking durations on private property. For private users, the low public charging demand shifts from the outer city to the city center. Private users in this scenario typically live in the outer city. Public charging demand is highly dispersed in the city center. Similarly, charging demand of commercial users shows a broader distribution for the urban area in the “Trend-DC” scenario, and the focus on outer city areas is less pronounced than in the “Baseline” and “Trend-AC” scenarios (Figure 8).

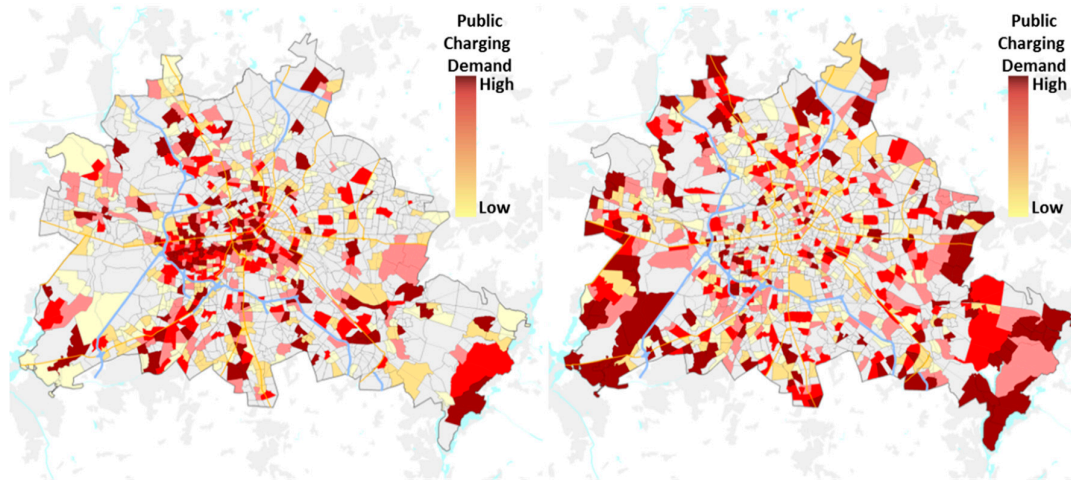


Figure 8. Relative spatial distribution of public charging demand: “Trend-DC” for private users (left, Pathway 3P) and commercial users (right, Pathway 3C).

3.2.4. “Accelerated” for Private Users

Including users without private infrastructure increases public charging demand for private users from less than 200 km per day to around 70,000 km per day. This corresponds to approximately 450 vehicles that are being fully charged every day in public areas. The traffic district with the highest demand has on average, three private vehicles fully charged per day using public infrastructure. More than one vehicle per day is charged in 130 traffic districts, and more than one vehicle is charged every two days in an additional 400 traffic districts. The spatial distribution of the charging demand shifts from the destination-related areas in the city center and outer city to residential and work-related areas (Figure 9).

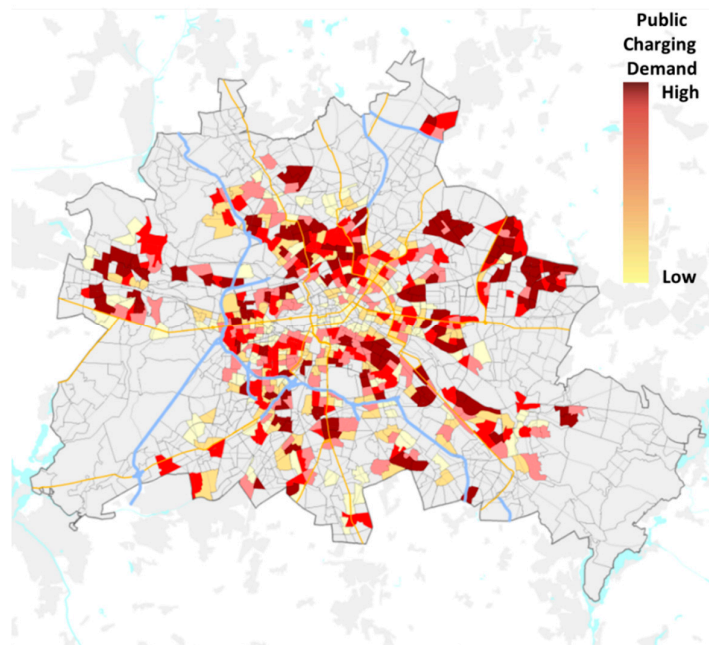


Figure 9. Relative spatial distribution of public charging demand: “Accelerated” for private users (Pathway 4P).

3.2.5. “Autonomous Driving” for Private Users

In the “Autonomous Driving” scenario, public charging demand of private users is slightly lower than the increase in fleet size. The spatial distribution of public charging demand remains

constant for private users, resulting mainly from users without private infrastructure. Due to the higher range, private users with their own infrastructure have a significantly lower demand for public charging. Demand for private users increases disproportionately compared to the fleet size increase.

3.2.6. “Baseline,” “Trend-AC,” and “Trend-DC” for Carsharing Users

The carsharing vehicles generate the highest public charging demand in all scenarios compared to the other user groups. In contrast to private and commercial users, Figure 10 uses color coding for the area of operation of carsharing vehicles (these vehicles do not operate everywhere in Berlin). Only the 290 traffic districts with the highest charging demand (of a total 583 traffic districts in the carsharing operational area) are highlighted in color; the low demand traffic districts are left blank.

Scenarios “Baseline” and “Trend-AC” for carsharing users has charging demand focused on the operational areas of the city center. This reflects the approach that only origin-destination-relations within the operational areas are made as carsharing trips. At the end of the trip, if required, charging processes are initiated according to the charging behavior model “empty and charge.” The highest demand arises in traffic districts with high terminating traffic, due to leisure and errand trips. In the traffic district with the highest public charging demand for the “Baseline” scenario, there is the charging demand of one charge per day with 110 km or about 11 hours of AC charge.

In the “Trend-AC” scenario the carsharing fleet increases from 306 to 500 vehicles. Due to the fleet expansion, more of the existing travel demand for carsharing trips can be completed. Reducing the time until the carsharing vehicles are relocated results in higher utilization of the vehicles. As the absolute public charging demand increases, the spatial distribution of the charging demand remains constant compared to the “Baseline” scenario. The charging demand in the traffic district with the highest demand is around 6.5 vehicles, each with a range of 110 km or 73 hours of AC charge.

In the “Trend-DC” scenario, technology development (i.e., DC charging) allows for faster charging. As a consequence, more trips can be completed with these vehicles. This increases the absolute number of trips made and the charging demand. Per vehicle and day, about 30 trips are carried out. The charging demand is about 15% higher than the “Trend-AC” scenario. The spatial distribution of the charging demand remains almost constant. The charging demand in the district with the highest demand is now about 7.5 charges, each with 110 km or about 1.5 hours of DC charge.

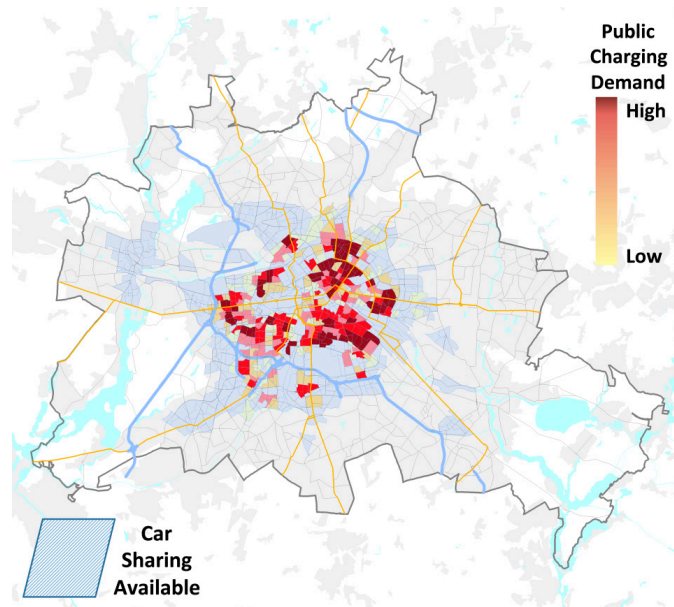


Figure 10. Relative spatial distribution of public charging demand: “Trend-AC” for carsharing users (Pathway 2CS); “Baseline” and “Trend-DC” are similar. Carsharing is only available in the highlighted area.

3.2.7. “Accelerated” for Carsharing

In the “Accelerated” scenario, the carsharing operational area is extended to the entire city. The fleet remains constant at 500 vehicles. Because of this, more trips are carried out, resulting in increased charging demand. The spatial distribution of the charging demand is more broadly distributed over the city compared to the scenarios “Baseline” and “Trend” (Figure 11). The utilization of the vehicles continues to increase to about 50 trips per day and vehicle. The highest charging demand is still in the city center, but there are also high charging demands in parts of the outer city. In the traffic district with the highest demand, there is a daily average of approximately six charges of 110 km each or a total of approximately 70 minutes of DC charge.

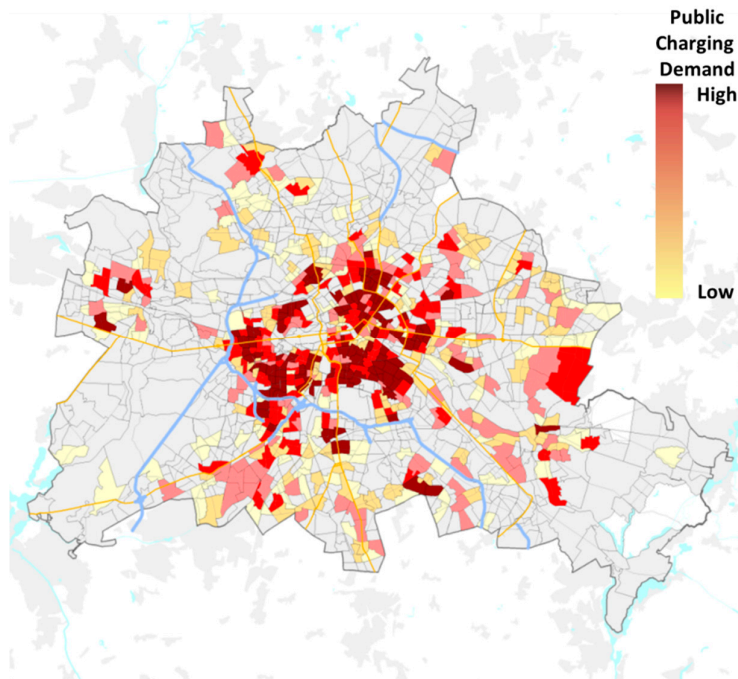


Figure 11. Relative spatial distribution of public charging demand: “Accelerated” for carsharing users (Pathway 4CS). Carsharing is available in the entire city.

3.2.8. “Autonomous Driving” for Carsharing Users

The “Autonomous Driving” scenario includes the fleet expansion of carsharing vehicles from 500 to 5,000, a range increase from 150 to 350 km, and autonomous carsharing vehicles. In this scenario, all requested trips can be carried out, and each vehicle drives about 100 km per day for 10 trips. This reduces the capacity utilization of the individual vehicles due to the fleet expansion compared to the “Accelerated” scenario. The charging demand increases fourfold. The relative spatial distribution remains constant (Figure 12). In the traffic district with the most demand, there is an average workday demand for seven full charges each of 340 km and a total of approximately 4 hours of DC charge.

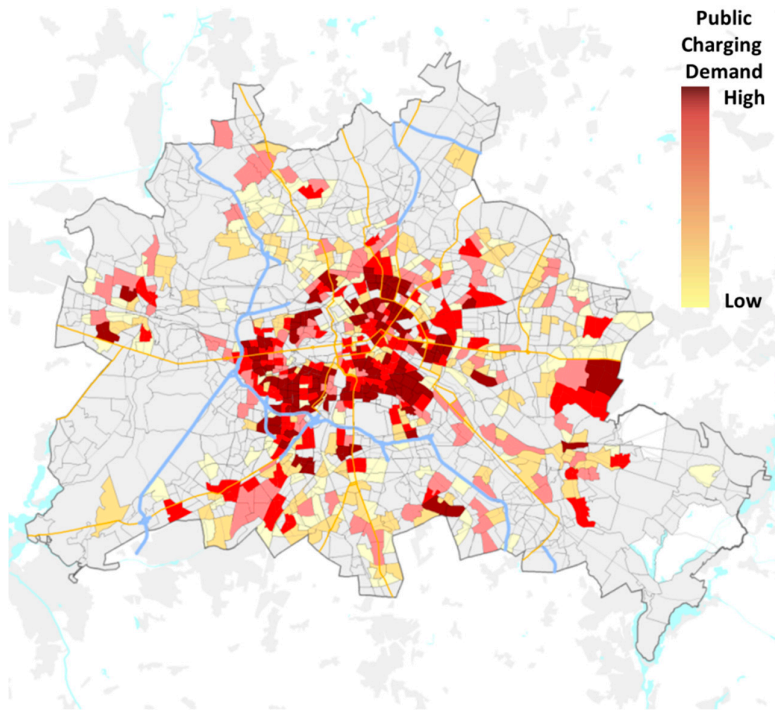


Figure 12. Relative spatial distribution of public charging demand: “Autonomous Driving” for carsharing users (Pathway 5CS). Carsharing is available in the entire city.

Table 2 gives an overview of the results. It shows the top five cells with the highest demand in each pathway. For detailed descriptions of the pathways see Table 1. Furthermore, it indicates the spatial location (inside or outside the inner city) of the according cell. As seen, the top five cells for the user group carsharing are located in the inner city for all scenarios. For private and commercial users, most of the top five locations lie outside the inner city.

Table 2. The top five cells with the most demand for each pathway. The percentage value indicates the share of the total demand in the pathway in the according cell. Location indicates the spatial location inside or outside the inner city.

1. Baseline								
1P			1CS			1C		
Cell-ID	Share	Location	Cell-ID	Share	Location	Cell-ID	Share	Location
110913712	2.38%	Outside	110310711	0.99%	Inside	110913913	1.87%	Outside
110100525	1.56%	Inside	110311011	0.75%	Inside	110913911	1.56%	Outside
111209612	1.43%	Outside	110311111	0.73%	Inside	110913814	0.99%	Outside
110707211	1.28%	Outside	110211621	0.67%	Inside	111019111	0.93%	Outside
110404421	1.12%	Inside	110211525	0.67%	Inside	110913512	0.89%	Outside
2. Trend-AC								
2P			2CS			2C		
Cell-ID	Share	Location	Cell-ID	Share	Location	Cell-ID	Share	Location
110913712	2.38%	Outside	110310711	1.12%	Inside	110913913	1.97%	Outside
110100525	1.61%	Inside	110311111	0.81%	Inside	110913911	1.56%	Outside
111209612	1.43%	Outside	110211613	0.75%	Inside	110913512	1.07%	Outside

110707211	1.28%	Outside	110311011	0.75%	Inside	111019111	1.01%	Outside
110404421	1.12%	Inside	110211525	0.73%	Inside	110913814	0.94%	Outside

3. Trend-DC

3P			3CS			3C		
Cell-ID	Share	Location	Cell-ID	Share	Location	Cell-ID	Share	Location
110913611	3.47%	Outside	110310711	1.09%	Inside	110913913	2.55%	Outside
110604922	3.26%	Outside	110311111	0.81%	Inside	110913911	2.51%	Outside
110912512	1.83%	Outside	110211621	0.77%	Inside	111019111	1.62%	Outside
110605322	1.60%	Outside	110211525	0.75%	Inside	110913512	1.43%	Outside
110315614	1.57%	Outside	110311011	0.75%	Inside	110913812	1.18%	Outside

4. Accelerated

4P			4CS			4C		
Cell-ID	Share	Location	Cell-ID	Share	Location	Cell-ID	Share	Location
110808223	0.58%	Outside	110310711	0.57%	Inside	110913913	2.55%	Outside
110808341	0.55%	Outside	110807513	0.49%	Inside	110913911	2.51%	Outside
110502744	0.52%	Outside	110201413	0.48%	Inside	111019111	1.62%	Outside
111209633	0.50%	Outside	110211621	0.48%	Inside	110913512	1.43%	Outside
111117522	0.48%	Outside	110211613	0.47%	Inside	110913812	1.18%	Outside

5. Autonomous

5P			5CS			5C		
Cell-ID	Share	Location	Cell-ID	Share	Location	Cell-ID	Share	Location
110808223	0.59%	Outside	110807513	0.49%	Inside	110913224	4.60%	Outside
110808341	0.56%	Outside	110310711	0.48%	Inside	110913812	2.14%	Outside
110502744	0.53%	Outside	110201413	0.42%	Inside	110310613	1.87%	Inside
111209633	0.52%	Outside	110211621	0.41%	Inside	110808334	1.74%	Outside
111117522	0.48%	Outside	110211613	0.41%	Inside	110605322	1.63%	Outside

4. Discussion

The results show a strong variance of charging demand, as well as spatial distribution for the different pathways. Regarding total charging demand, the results show that carsharing generates by far the highest public charging demand in all scenarios: 62% in the “Accelerated” scenario to 97% in the “Trend-DC” scenario. In the “Baseline” and the trend scenarios (i.e., “Trend-AC”, “Trend-DC”) private users’ charging demand makes up only 1% of the demand in public areas. This reflects the modeled behavior as electric vehicle users prefer their own private charging infrastructure. With technical progress (i.e., fast-charging and increased range), the share of public charging for private and commercial users declines. Long charging events at private infrastructure (e.g., overnight at home) result in an increased range, due to the larger battery size. Furthermore, vehicles can charge faster at private charging infrastructure so the vehicles can be charged more often, even in short breaks. Due to both these factors public intermediate charging becomes less critical.

Allocating electric vehicles to private users without private charging infrastructure dramatically increases public charging demand. For the “Accelerated” scenario, the share of private users charging at public infrastructure increases to 37% of the total demand at public stations. For commercial users, the slightly higher share of public charging in the “Baseline” and the “Trend-AC” scenario decreases significantly with technical progress (from about 7% to about 3%). This reflects the modeling of commercial vehicles: they have more frequent and longer trips than private users. More than 1,000 trip chains have a daily mileage of more than 150 km and up to 600 km.

With regard to the spatial distribution of the charging demand, some fundamental trends are recognizable. First, for commercial users, the very low public charging demand tends to be concentrated in the outer city. Second, for private users initially (i.e., “Baseline” scenario), their main charging demand is located in the city center and in the outer city. Third, having more users without private charging infrastructure and over the course of technological development, the spatial distribution of charging demand continues to concentrate in the city center. Finally, for flexible carsharing, the bulk of the charging demand remains in the city center even when carsharing becomes much more popular and widespread for increasing and diverse users, as well as an expansion to a citywide operational area.

The results highlight the importance of the user-centric approach, using appropriate data sources and simulation methods. The needs and behavior of different user groups vary significantly. As seen, this leads to significant differences in both charging demand and spatial distribution. This enhances the value of the results of the user-centric approach compared to traffic flow analyses as discussed above. Furthermore, the quantity and spatial distribution of charging demand vary in different future scenarios making it important to consider future developments.

The limitations of the study are as follows. Mixed charging technology (i.e., both AC and DC charging) has not been modeled. For example, a scenario could allow for slow private charging and fast public charging. In addition, sensitivity analyses could evaluate the impact share of fast-charging in a mixed public infrastructure. Due to the data sources and models, commuters from outside the city and long-distance traffic are not included in the study.

5. Conclusions and Policy Implications

We present an approach to estimate the charging demand for electric vehicles in an urban setting for various user groups and future development pathways. The results show that the approach is suitable for demand-oriented planning of public charging infrastructure. Our main findings are as follows. First, for demand-based planning, knowledge of users is indispensable as spatial priorities, and the total amount of charging stations needed vary strongly among different user groups and future pathways. Second, the availability of private charging infrastructure is crucial when determining public charging demand. Private infrastructure strongly influences the number of charging stations needed and affects the spatial distribution of charging demand. Third, city-centered public charging infrastructure is a future-oriented means of providing demand-oriented infrastructure.

Based on the results, there are several recommendations for public infrastructure for electric vehicles. First, when expanding charging infrastructure, attention should be paid to technical developments and user behavior as they both strongly affect the amount and spatial distribution of charging demand. Second, private charging infrastructure should be supported as users without private charging infrastructure dramatically increase the need for public charging infrastructure. Third, focusing on the expansion of public charging infrastructure in the city center is a future-oriented means of providing demand-oriented infrastructure. Fourth, additional stations should be considered in selected areas in the outer city. The target users should always be clearly identified and the development of local forecast needs must be taken into account. Fifth, given the enormous differences in total charging demand for different user groups, a political decision on which users to address is necessary, especially when dealing with limited resources.

In addition, the findings of the paper can be transferred to cities similar to the case study of Berlin. In particular, the relative distribution of charging demand, the spatial distribution of demand for user groups, and the differences in demand for future pathways are transferable. Hence the results can be utilized as an approximation of charging demand for other cities without extensive additional models and simulations.

Author Contributions: M. Hardinghaus was responsible for the derivation of user behavior data and the scenario development. C. Seidel was responsible for the development and execution of the demand oriented simulation of user group specific behavior. J. Anderson was responsible for developing the paper concept, conducting the literature review, and writing the paper.

Funding: The research was conducted within the project PlaG-inn: Demand-oriented planning, efficient approval, innovation-oriented procurement and private financing of charging infrastructure. The project was funded by the German Federal Ministry of Transport and Digital Infrastructure.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Nordelöf, A.; Messagie, M.; Tillman, A.; Ljunggren Söderman, M.; Van Mierlo, J. Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—What can we learn from life cycle assessment? *Int. J. Life Cycle Assess.* **2014**, *19*, 1866–1890, doi:10.1007/s11367-014-0788-0.
2. Holland, S.P.; Mansur, E.T.; Muller, N.Z.; Yates, A.J. Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. *Am. Econ. Rev.* **2016**, *106*, 3700–3729, doi:10.1257/aer.20150897.
3. Archsmith, J.; Kendall, A.; Rapson, D. From Cradle to Junkyard: Assessing the Life Cycle Greenhouse Gas Benefits of Electric Vehicles. *Res. Transp. Econ.* **2015**, *52*, 72–90, doi:10.1016/j.retrec.2015.10.007.
4. Allison, W.; Paulina, J.; Jeremy, M. Consequential life cycle air emissions externalities for plug-in electric vehicles in the PJM interconnection. *Environ. Res. Lett.* **2016**, *11*, 024009.
5. Tugce, Y.; Mili-Ann, M.T.; Chris, H.; Inês, M.L.A.; Jeremy, J.M. Effect of regional grid mix, driving patterns and climate on the comparative carbon footprint of gasoline and plug-in electric vehicles in the United States. *Environ. Res. Lett.* **2016**, *11*, 044007.
6. Barisa, A.; Rosa, M.; Kisele, A. Introducing electric mobility in Latvian municipalities: Results of a survey. *Energy Procedia* **2016**, *95*, 50–57, doi:10.1016/j.egypro.2016.09.015.
7. Rahman, I.; Vasant, P.M.; Singh, B.; Singh, M.; Abdullah-Al-Wadud, M.; Adnan, N. Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1039–1047, doi:10.1016/j.rser.2015.12.353.
8. Dong, J.; Liu, C.; Lin, Z. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. *Transp. Res. Part C Emerg. Technol.* **2014**, *38*, 44–55, doi:10.1016/j.trc.2013.11.001.
9. Cavadas, J.; Homem de Almeida Correia, G.; Gouveia, J. A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. *Transp. Res. Part E Logist. Transp. Rev.* **2015**, *75*, 188–201, doi:10.1016/j.tre.2014.11.005.
10. Brooker, R.P.; Qin, N. Identification of potential locations of electric vehicle supply equipment. *J. Power Sources* **2015**, *299*, 76–84, doi:10.1016/j.jpowsour.2015.08.097.
11. Paffumi, E.; De Gennaro, M.; Martini, G.; Scholz, H. Assessment of the potential of electric vehicles and charging strategies to meet urban mobility requirements. *Transp. A Transp. Sci.* **2015**, *11*, 22–60, doi:10.1080/23249935.2014.913732.
12. Chen, T.D.; Kockelman, K.M.; Khan, M. The electric vehicle charging station location problem: A parking-based assignment method for Seattle. In Proceedings of the Transportation Research Board 92nd Annual Meeting, Washington, DC, USA, 13–17 January 2013; p. 14.
13. Helmus, J.; van den Hoed, R. Unraveling User Type Characteristics: Towards a Taxonomy for Charging Infrastructure. In Proceedings of the Conference EVS28, Goyang, Korea, 3–6 May 2015.
14. Yang, W. A user-choice model for locating congested fast charging stations. *Transp. Res. Part E* **2018**, *110*, 189–213, doi:10.1016/j.tre.2017.11.009.
15. Gnann, T.; Funke, S.; Jakobsson, N.; Plötz, P.; Sprei, F.; Bennehag, A. Fast charging infrastructure for electric vehicles: Today's situation and future needs. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 314–329, doi:10.1016/j.trd.2018.03.004.
16. Gnann, T.; Plötz, P.; Wietschel, M. Can public slow charging accelerate plug-in electric vehicle sales? A simulation of charging infrastructure usage and its impact on plug-in electric vehicle sales for Germany. *Int. J. Sustain. Transp.* **2019**, *13*, 528–542, doi:10.1080/15568318.2018.1489016.
17. Li, S.; Huang, Y. Optimal Design of Electric Vehicle Charging Infrastructure Network—A Case Study of South Carolina. In Proceedings of the Transportation Research Board 94th Annual Meeting, Washington, DC, USA, 11–15 January 2015; p. 16.
18. He, F.; Yin, Y.; Zhou, J. Deploying public charging stations for electric vehicles on urban road networks. *Transp. Res. Part C Emerg. Technol.* **2015**, *60*, 227–240, doi:10.1016/j.trc.2015.08.018.

19. Olivella-Rosell, P.; Villafafila-Robles, R.; Sumper, A.; Bergas-Jané, J. Probabilistic Agent-Based Model of Electric Vehicle Charging Demand to Analyse the Impact on Distribution Networks. *Energies* **2015**, *8*, 4160–4187, doi:10.3390/en8054160.
20. Sathaye, N.; Kelley, S. An approach for the optimal planning of electric vehicle infrastructure for highway corridors. *Transp. Res. Part E Logist. Transp. Rev.* **2013**, *59*, 15–33, doi:10.1016/j.tre.2013.08.003.
21. Lam, A.Y.S.; Yiu-Wing, L.; Xiaowen, C. Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions. *IEEE Trans. Smart Grid* **2014**, *5*, 2846–2856, doi:10.1109/TSG.2014.2344684.
22. Tian, Z.; Hou, W.; Gu, X.; Gu, F.; Yao, B. The location optimization of electric vehicle charging stations considering charging behavior. *Simulation* **2018**, *94*, 625–636, doi:10.1177/0037549717743807.
23. Chen, C.; Hua, G. A New Model for Optimal Deployment of Electric Vehicle Charging and Battery Swapping Stations. *Int. J. Control Autom.* **2014**, *7*, 247–258, doi:10.14257/ijca.2014.7.5.27.
24. Frade, I.; Ribeiro, A.; Gonçalves, G.; Antunes, A.P. Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. *Transp. Res. Record* **2011**, *2252*, 91–98, doi:10.3141/2252-12.
25. Nie, Y.; Ghamami, M. A corridor-centric approach to planning electric vehicle charging infrastructure. *Transp. Res. Part B Methodol.* **2013**, *57*, 172–190, doi:10.1016/j.trb.2013.08.010.
26. Yao, E.; Yang, Q.; Yang, Y.; Zhang, Y. Charging Demand-Based Electric Vehicles' Quick Charging Station Layout Planning. In Proceedings of the Transportation Research Board 94th Annual Meeting, Washington DC, USA, 11–15 January 2015.
27. Jung, J.; Chow, J.; Jayakrishnan, R.; Park, J. Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations. *Transp. Res. Part C* **2014**, *40*, 123–142, doi:10.1016/j.trc.2014.01.008.
28. BMWi (Federal Ministry for Economic Affairs and Energy). Energy Concept for an Environmentally Friendly, Reliable and Affordable Energy Supply. 2010. Available online: https://www.bmwi.de/Redaktion/DE/Downloads/E/energiekonzept-2010.pdf?__blob=publicationFile&v=3, (accessed on 10 October 2019).
29. German Federal Government. A New Departure for Europe, A New Dynamic for Germany, A New Cohesion for Our Country—Coalition Agreement between the CDU, CSU und SPD, 19th Legislature period, 2018. Available online: https://www.cdu.de/system/tdf/media/dokumente/koalitionsvertrag_2018.pdf?file=1 (accessed on 10 October 2019).
30. KBA (Federal Motor Transport Authority). Press Release—Vehicle Registrations in 2019. 2019. Available online: https://www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/MonatlicheNeuzulassungen/monatl_neuzulassungen_node.html?sessionid=6E2265E4957FB0F5FFC465463D293854.live21303 (accessed on 10 October 2019).
31. Heinrichs, M.; Krajzewicz, D.; Cyganski, R.; von Schmidt, A. Disaggregated car fleets in microscopic travel demand modeling. In Proceedings of the 7th International Conference on Ambient Systems Networks and Technologies (ANT), Madrid, Spain, 23–26 May 2016, doi:10.1016/j.procs.2016.04.111.
32. PTV Planung Transport Verkehr AG. *PTV VISUM 15*; PTV AG: Karlsruhe, Germany, 2015.
33. Ahrens, G.-A.; Ließke, F.; Wittwer, R.; Hubrich, S. *Final Report on Traffic Survey 'Urban Mobility—SrV 2008' and Evaluations of SrV City Level*; Technische Universität Dresden, Dresden, 2009, pp. 157–157.
34. Schneider, S.; Wolfermann, A. Estimating service related traffic demand from trip chain data. In Proceedings of the Transportation Research Board 92nd Annual Meeting, Washington, DC, USA, 13–17 January 2013.
35. Frenzel, I.; Jarass, J.; Trommer, S.; Lenz, B. *First-Time Users of Electric Vehicles in Germany. User Profiles, Purchase, Vehicle Usage*; Aerospace Center: Berlin, German, 2015. Available online: https://www.dlr.de/vf/Portaldata/12/Resources/dokumente/projekte/pakt2/Ergebnisbericht_E-Nutzer_2015.pdf (accessed on 10 October 2019).
36. Müller, J.; Schmöller, S.; Giesel, F. Identifying Users and Use of (Electric-) Free-Floating Carsharing in Berlin and Munich. In Proceedings of the 18th IEEE International Conference on Intelligent Transportation Systems (ITSC), Gran Canaria, Spain, 15–18 September 2015; pp. 2569–2573, doi:10.1109/ITSC.2015.413.
37. Kihm, A.; Trommer, S. The new car market for electric vehicles and the potential for fuel substitution. *Energy Policy* **2014**, *73*, 147–157, doi:10.1016/j.enpol.2014.05.021.

